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A STUDY ON AI -POWERED RECOMMENDER SYSTEMS ON EXPANDING E-WOM AND IMPACT OF E-WOM FOR SOCIAL CAUSES RELATED MARKETING

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Abstract
Recommender systems are often used to customize suggestions to individual users. As the amount of data available online continues to swell, recommender systems have shown to be an effective method of dealing with the resulting information overload. The promise of recommender systems to alleviate many problems caused by too many options is too great to ignore. Different recommendation systems use unique approaches and principles. Many industries, from business and medicine to transportation and agriculture to the media, have begun using recommendation systems. In this article, we provide the state of the art in the study of recommender systems and point the way forward for the topic in a variety of contexts. This article presents the results of a research into the effects of e-WOM and AI-powered recommendation systems on the growth of e-WOM and the promotion of social causes.

1. Introduction

The exponential development of AI is having an impact on the present and future of every person, every sector, and the global economy as a whole. Although artificial intelligence (AI) has been a cutting-edge topic of study for over fifty years, its last decade of rapid growth has been particularly noteworthy[1]. Future innovative marketing apps will rely heavily on AI for things like content recommendation engines, ad targeting, predictive analytics, and chatbots. It's possible that some of these programmes will end up being crucial to our development as a species[2].

Since gathering and analysing consumer data provides enormous benefits, businesses, academics, and government agencies have demonstrated a growing interest in AI-based technology and predictive analytics in recent years. Artificial intelligence (AI) marketing applications have grown significantly, allowing businesses to better understand their consumers, better target them, and make more educated marketing and strategic choices. By removing the financial burden of testing out new models and techniques, these technologies empower internet marketers to target the correct audience on social media sites like Facebook.

To be more specific, AI-designed recommendation systems are typically defined as a subset of an information filtering system that aggregates information from various sources via algorithms to predict consumer preferences for products or services and then provides related indications in the form of advice [4]. Because of the thoughtful and effective design of these recommendation engines, businesses now have access to a wealth of information about their consumers' shopping habits and interests. As a result, businesses may utilise this information to improve their interactions with customers and their customers' overall buying experiences. In addition, recommendation systems may provide clients tailored recommendations, which can simplify the decision-making process and improve the overall shopping experience. Many businesses are quickly adopting AI-designed recommendation systems because of how well they can provide customised recommendations for both consumers and the business itself.

Researchers have looked at the effects of both traditional WOM and EWOM, or electronic word of mouth, on consumers' decisions to buy a product or use a service [5,6]. Buyers of new services or products often rely on recommendations from friends and family[8,9]. The fact that EWOM often lack any selling aim like in commercials [10,11] is one reason why consumers trust EWOM for acquiring information, especially when they are in the process of purchasing. Previous and current research have indicated that the influence of EWOMs is far greater than that of regular advertisements[12].EWOM refers to the online buzz about a certain brand or service. More people could get the data in a short amount of time thanks to the Internet.

The term "Cause Related Marketing" (CRM) refers to the combination of product promotion and CSR. Researching cause-related marketing on a worldwide scale is important because “the type and extent of the needs expected to be fulfilled from the socially responsible firm will depend upon the culture and ethics of the social segment, the legal environment, and the degree to which the members of the social segment perceive that such needs are not fulfilled”[13].Therefore, we will be conducting our studies primarily in three areas: marketing for a good purpose, online word-of-mouth, and artificial intelligence-driven recommendations.

2 Review of Literature

2.1 AI-designed Recommendation Systems

The design of AI-based recommendation systems may take a number of forms, each of which employs a unique set of principles, methods, and assumptions. Collaborative filtering, content-based filtering, and hybrid models are the most popular variants. In specifically, collaborative filtering provides suggestions for consumers by aggregating data not just from the user but also from other users whose purchasing and rating histories are comparable to the user's own. If a user has shown an interest in a certain kind of material in the past, a content-based filtering system will suggest other content that may also be of interest. The algorithm uses the user's personal information in conjunction with keywords used to describe the goods to determine a user's preferences [14].

Cold-start is a concern for both of the aforementioned system types. When an engine first encounters a fresh set of users or a new set of things, this scenario is known as a "cold start," because it results in unreliable suggestions. Lack of data, or data sparsity, is a related issue with the same root cause. This effect is most common when a user has few ratings and reviews to draw from, as well as little details about what they like and don't like.

Hybrid models are the result of combining several types of systems. This has the potential to enhance suggestion precision while also resolving problems associated with data scarcity and a cold start. Hybrid strategies may provide more precise direction and improve decision quality, according to the results of many empirical studies that compare the hybrid model's efficacy to that of collaborative and content-based approaches.

Several alternative models exist as well, with most of them concentrating on providing users with recommendations for material based on their specific context. The outputs vary because each model offers a unique combination of costs and advantages to the customer.

All types of AI-created recommendation systems rely heavily on a machine-learning algorithm for its core suggestion mechanism. Recommendation engines have become straightforward and efficient because to the incorporation of big data and machine learning. In addition to helping users, using AI in recommendation systems may be useful for businesses as well, thanks to the data it can collect about customers' interests [15–17]. Users no longer have to waste time looking for information because of this technology [18].

2.2 Electronic Word-of-Mouth (EWOM)

The consumer literature [8,19,20] acknowledges and confirms the persuasiveness of word-of-mouth advertising. Consumers place more stock in recommendations from friends and family than they do in advertisements in newspapers, magazines, on television, and elsewhere, according to past research. The proliferation of the Internet has allowed for the expansion of EWOM communication to a wide variety of new virtual structures, all of which contribute to the persuasive effect of WOM on purchase intent. Blogs (like xanga.com), forums (like zapak.com), review oriented websites (like Epinions.com), newsgroups (like facebook.com), and social networking sites (like fb.com) are all places where consumers share their thoughts on items and services they have purchased[21].

E-WOM refers to the "informal method of communication amongst people, in relation to a brand, a product/service, or a company" [22] and has emerged as a result of the proliferation of both the internet and electronic communication. According to Wu and Wang [23], EWOM is defined as "the sharing of information between a company and its customers, both current and potential."

Henning-Thurau et al. [24] defined EWOM as "any opinion, favourable or unfavourable, expressed by a consumer and disseminated via electronic channels." Consumers may connect with both familiar and unfamiliar faces in online communities, where they can discuss and rate goods and services.

Blogs, review-based sites, social networking sites, and online forums are just some of the digital platforms that have altered the way word-of-mouth (WOM) is spread from one person to another, as noted by Lopez and Sicilia[26].

The ability to communicate is fundamental to being human. When people get together for coffee, speak on the phone, send each other emails, or have online conversations, they share a lot of information with one another every day. Customers are more likely to believe EWOM than they are to trust TV, print, or web advertising because EWOM comes from real people rather than corporations [27]. Customers' own words carry more weight and are more likely to be believed than those of a business [28].

2.3 Cause related marketing

As per Rajput[29] "the research on cost related marketing as co correlate of brand choice may also be undertaken in other industries,". Learning the distinction between Corporate Social Responsibility (CSR) and Cause Related Marketing (CRM) requires a firm grasp of both concepts. CSR was first defined by Bowen in his article, and Spokane, Washington native Carroll [30] is often regarded as the concept's progenitor. "Corporate social responsibility" (CSR) "refers to the duties of businesses to pursue those policies, make those choices, or follow those courses of action which are beneficial in terms of the purposes and values of society." According to Kawamura[31], CSR is the practise of placing an emphasis on the ethical and social aspects of business operations, including but not limited to: legal compliance, corporate ethics, corruption, labour, human rights, hygiene, social contribution, consumer protection, international operations and procurement standards . On the other hand, cause-related marketing (CRM) is described as the planning and execution of marketing operations that include making a donation to a charitable cause in return for potential consumers' purchases or other financial transactions with the business.

Corbishley and Mason[32] surveyed 400 people at shopping malls using a pre-tested questionnaire. The study's findings revealed a correlation between demographic information and interest in a CRM's services.

In their research, Sheikh and Zed [33] found that CSR and CRM do influence consumers' perspectives. They also highlighted that although CRM might be cheaper in the long run, its benefits are restricted to clients who already have a strong connection to the cause. The opposite is true for consumers who have low cause affinity or who actively reject the cause. In addition to the company's exterior customers, CRM also has an impact on the company's internal customers, namely the staff. Employees have a favourable impression of the company as an employer, and the business and non-business communities see the company favourably due to its participation in cause-related activities.

3. Objective

Main objectives of this study are discussed below

1) To examine Impact of AI -Powered Recommender Systems on Expanding e-WOM
2) impact of E-WOM for Social Causes related marketing

4. Research Methodology

There are two aspects to the methodology of this research. The first part will go over the algorithm-based strategy used for an AI-powered recommendation system to expand E-WOM, while the second will go over the survey-based approach used to describe the influence of E-WOM on social cause-related marketing..

4.1 AI powered Recommendation methodology

A) Tensor Flow Recommender System (TFRS)

Tensor Flow Recommender (TFRS) is an open-source Tensor Flow package that makes building, evaluating, and serving sophisticated recommender models easy. It is an end-to-end recommender system.

- Built with TensorFlow 2.x and Keras.
- Provides a set of components for building evaluating, deploying recommender model.
- Aims at covering the entire strack, from retrieval, through ranking, to post-ranking.

The purpose of a recommender system is to find a few high-quality suggestions from millions or even tens of millions of possible options.Recommendation candidates are chosen during the retrieval stage.The top applicants are chosen and ranked in a ranking phase.

Tensorflow Using Recommendations, creating two-tower retrieval models is a breeze. Such models use a two-stage retrieval process:

1) it converts user-provided data into an embedding.

2) Identifying the best possible embedding candidates.

Computing the dot product of the user input and the candidate embedding is relatively cheap, but doing so for every embedding in a database, which scales linearly with the size of the database, quickly becomes computationally infeasible in the two-tower model. Therefore, it is essential for recommender systems to use a quick closest neighbour search technique.

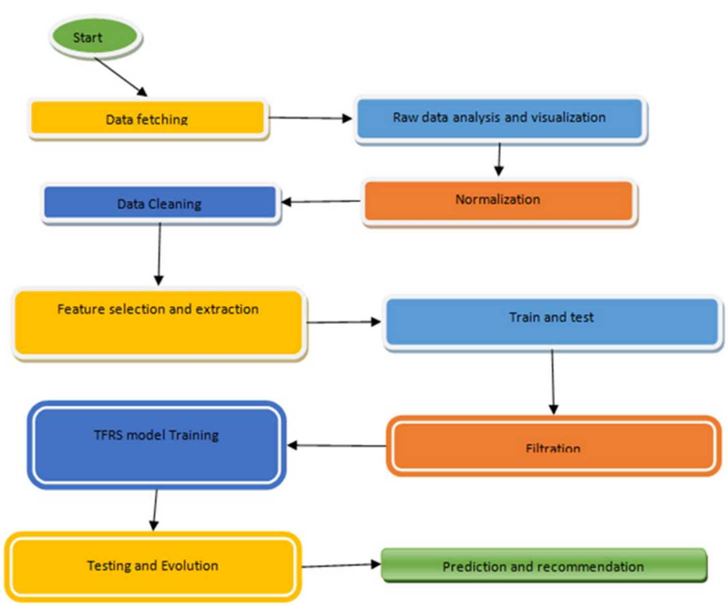


Figure 1: Flow chart of AI powered recommendation system

B) Dataset

E-commerce companies such as Flipkart and Amazon utilise a variety of recommendation methods to present users with individualised recommendations according to their specific interests. At this time, Amazon makes use of a method called item-to-item collaborative filtering, which is capable of scaling to enormous data sets and producing high-quality recommendations in real time. This sort of filtering compares each of the user's purchased and rated things to other items that are comparable to those items, and then compiles a list of recommendations for the user using just those items that are similar. Within the scope of this project, we are going to construct a recommendation model for the electrical goods sold on Amazon. Link: https://www.kaggle.com/datasets/saurav9786/amazon-product-reviews. The sample dataset is given in figure 4.1. The attributes in the dataset are User ID, Product ID, Rating and TimeStamp. The shape of the dataset is (1000000, 4).

4.2 Surveyed based approach

Data collection consisted of a questionnaire since this was an exploratory research. The population sample includes Internet shoppers. The research used a sample of 150 participants. The study used respondents as the sample components. The selection of respondents for inclusion in the sample did not follow statistically sound probability distributions. In order to gather information, we employed self-created questionnaires based on Likert scales. We asked for ratings on a scale from 1 (strongly disagree) to 5 (strongly agree), with 1 (not at all) being the most common answer.

5. Result and Discussion

5.1 Impact of AI -Powered Recommender Systems on Expanding e-WOM

A) Pre-processing

Normalisation is the initial stage of the pre-processing procedure. Normalisation is a common step in the process of getting machine learning-ready data. The goal of normalisation is to adjust the size of the dataset's numerical columns to get consistent results across the board. There shouldn't be any loss of information or distortion of the ranges of values as a result of this.

	ProductID	UserID	Rating	Time
1	AKM1MP6P0OYPR	132793040	5	1365811200
2	A2CX7LUOHB2NDG	321732944	5	1341100800
3	A2NWSAGRHCP8N5	439886341	1	1367193600
4	A2WNBOD3WNDNKT	439886341	3	1374451200
5	A1GI0U4ZRJA8WN	439886341	1	1334707200

Figure 2: Sample dataset

	Time	Rating
0	2014-07-14	292
1	2014-07-15	211
2	2014-07-16	199
3	2014-07-17	71
4	2014-07-18	88
5	2014-07-19	70
6	2014-07-20	76
7	2014-07-21	95
8	2014-07-22	91
9	2014-07-23	11

Figure 3: Normalized dataset

Next the raw Data Rating Analysis is taking place by counting the index values and calculating the missing values. The number of yearly ratings is given in figure 4. It can be seen that the number of yearly rating is peaking at the year 2007. The rating counts is given in figure 5. The ratings are divided into 5 parts and it gives the number of ratings in the different 5 parts. The number of top products rated during period of 30 days is given in figure 6. It can be seen from the graph that throughout the period of 30 days, the average rating is higher than the number of ratings.

After analysing raw data, the next step is to clean the data. Data cleansing is the act of removing or updating data that is flawed in some way, such as being incorrect, corrupted, improperly structured, redundant, or missing. There is a higher possibility of data duplication and inaccurate labelling when data from many sources is merged. When looking for duplicates, we filter out the null values first. The Min-Max-Scalar is a useful tool for uniformity testing. After using Min max Scalar, it's clear that 1 is the lowest possible score and 5 is the most.

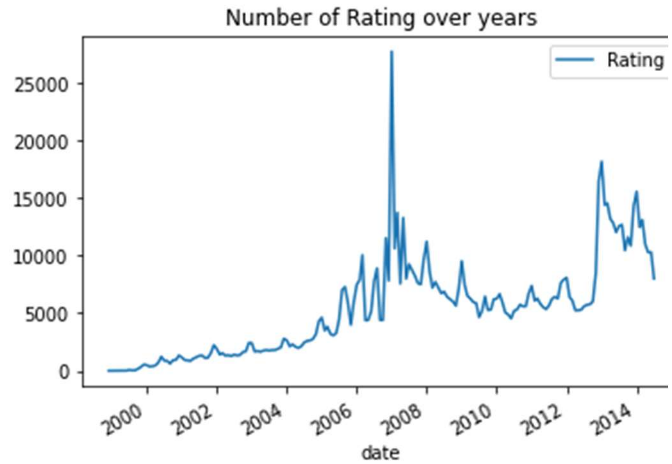


Figure 4: Yearly Ratings

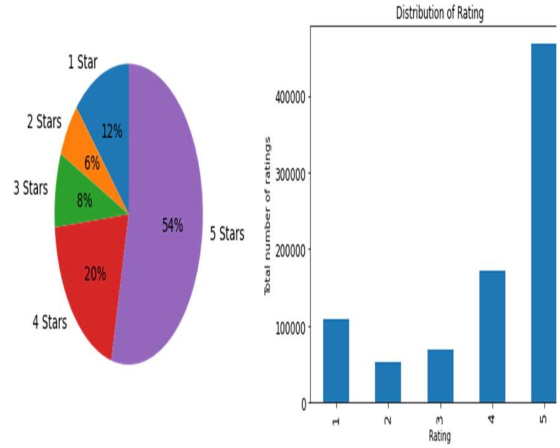


Figure 5: Rating Counts

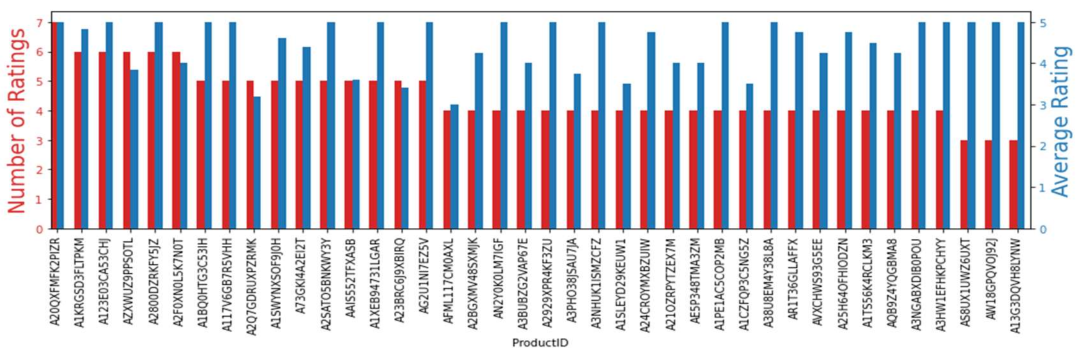


Figure 6: The number of top products rated during period of 30 days

B) Feature Selection and Extraction

Feature selection and extraction is taking place using the variance threshold algorithm. A feature selection known as Variance threshold is applied to a dataset in order to eliminate any characteristics with a low variance that are not very helpful for modelling. Unsupervised learning is possible because it concentrates solely on the inputs, or features, rather than on the outcomes, or outputs. The value 0 is used for the Threshold setting by default. Next, Finding the Constraint and Non-Constraint Values is taking place. The number of non constant feature is 3.

Corelation Confusion Matrix Heatmap of Training & Testing Data is considered. It is common practice to calculate correlation coefficients in order to investigate the degree to which certain quantitative variables are connected with one another. When one variable increases and the other also increases, we say that there is a positive correlation between the two variables. On the other hand, they are said to have a negative correlation when the high values of one variable are seen to go hand in hand with the low values of another variable. The number of correlated features is 2.

Figure 7 gives the correlation coefficient matrix. The data after feature selection and extraction is given in figure 8.

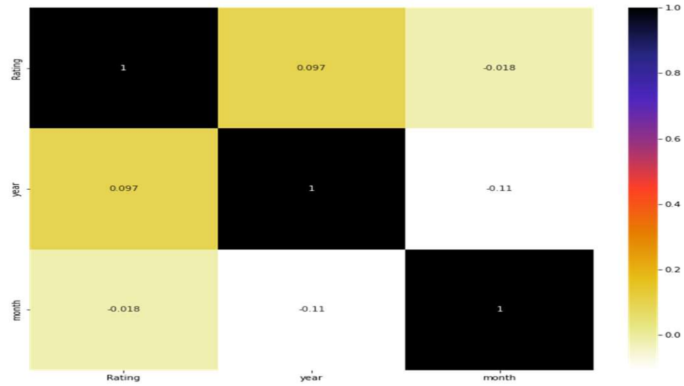


Figure 7: Correlation coefficient matrix

	ProductID	UserID	Rating
270117	A22FB2WSZSXSHH	059400232X	5
121806	A2WOJCFAWI8VS8	059400232X	5
42117	AZQZ3STMCBG5H	059400232X	5
599640	A2RMLNVKPFRK7X	089933623X	4
357568	AJ4QIAKKHW21N	089933623X	1

Figure 8 : Data After Feature Selection and Extraction

C) Training and testing of Tensor Flow Recommenders model

The Tensor Flow Recommender (TFRS) model is used as the recommendation system in the proposed system. For the recommendation system, the number of samples selected is 5000. The data is split into training, testing and validation data in the ratio, 70:20:10. They are split as ((3500, 2), (1000, 2), (500, 2), (3500, 1), (1000, 1), (500, 1)). The TFRS neural network model is configured and the model summary is created. The model loss Ratio Graph is given in figure 4.8. After training of the model, the testing and evaluation of the dataset takes place.

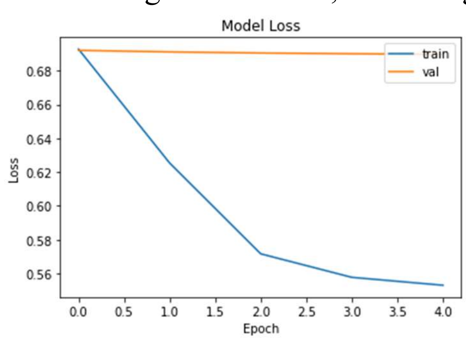


Figure 9: Model loss Ratio Graph

	ProductID	UserID	Rating	user	product
868204	A247MCYT5KRXMT	B00006HOLO	5.0	1000	1172
2330	A1WZZOQ19O1EOY	B00028ONIA	5.0	1089	3151
923903	A8POXH5C04GWF	B0001LGXO0	5.0	1013	1186
510794	A11N8EJIZ05LR8	B0001FTVDQ	5.0	1440	1810
645247	A1L2QNIGO6COCB	B000GBGPAW	5.0	545	610
877079	A3EIOGB0QIWASV	B00007EDZG	5.0	399	3161
369256	A67CNBDEZMHSM	B00009EHJV	4.0	1439	1809
948468	A109LWN9DUGPDP	B00008IP5F	5.0	2337	3163
174420	A3TA2NGIRLOOMK	B0000CCOVM	1.0	1451	1822
475688	A6IOX1DXPS0CN	B000G6M916	5.0	1443	1814

Figure 10: Record of Recommended Data

After testing and evaluation, the prediction and recommendation takes place. The top 10 recommendations for userID are given. The record of recommended data is given in figure 10.

D) Testing based on different scenarios

Using matrix factorization

Some More Testing is done based on Different Scenarios using Model with Matrix Factorization. Cosine similarity in the recommendation system follows the same principle as cosine angles, so the least recommended content would be the one with the highest cosine similarity and vice versa. Cosine values between 0 and 360 degrees are used to measure angles. Here, we investigate a recommender system with a matrix size of 4980 3324 that is based on users' cosine similarity. The prediction and recommendation is given in figure 11.

	ProductID	UserID	Rating
263443	A2J6L9MFRHDQX0	B000FZ292W	5
659253	A44EO3AUM4MYQ	B000BFNT0W	5
506492	A46MEW8NTP981	B000CSOXTO	5
754209	A2J5M252FNR8CX	B000GE77XS	5
158295	A3USCO6LEP0FQR	B000B69WVG	5
384623	A2IYD6W54M7HLH	B000FOYMKU	5
271611	A3XKRGYKOWYRE	B000BTL0OA	5
282984	AZX96MTMYA8DG	B000BQ7GW8	5
406751	A46DW8VOKJDCU	B000EPTA0C	5
675117	A2IPE2KFGTZMI3	B000BT97UO	5

Figure 11: Prediction and recommendation using matrix factorization

ProductID	Rating	ratings_count	ratings_average
A00038802J7X43YTW44TD	3.0	2	3.0
A000428226SAAAIBK8I36	5.0	1	5.0
A0004478EF5NFPHLGCWG	4.0	1	4.0
A000681618A3WRMCK53V	2.0	1	2.0
A00101847G3FJTWYGNQA	5.0	1	5.0

Figure 12 Average rating calculation

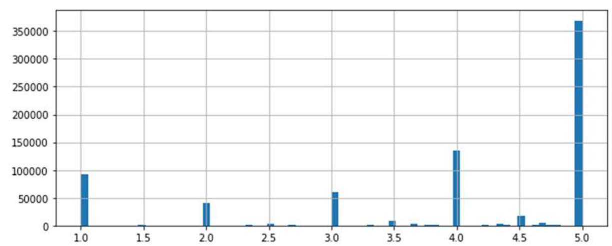


Figure 13: Rating Histogram

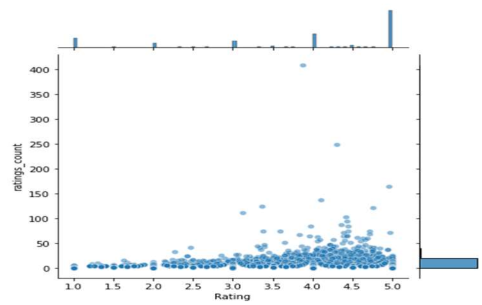
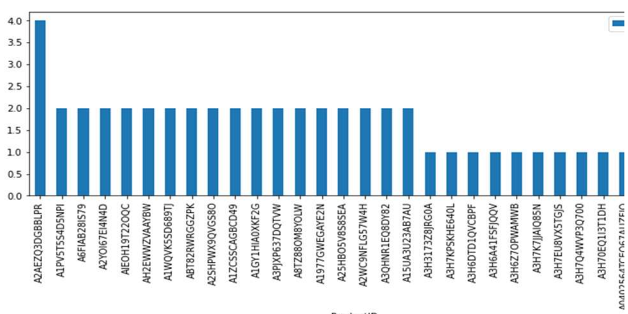


Figure 14: Correlation of Rating and Avg Rating based on Rating Count

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['A2SATO5BNKWY3Y',
 'A22W0MPWNJSWA1',
 'A2TZFY76KGMT1J',
 'A3959SFRR2PHMR',
 'A02970121VCH64N53W9F4',
 'A06374853B2OXBKB6H1YT',
 'A07324873GQMRSBW9534Y',
 'A08308746P79YA4578KB',
 'A100QCLQX5P0NR',
 'A101AH8PLZCTYO']
```

Figure 15: Top 30 Recommendation and their Rating Count

Recommendation based on Average Ratings Correlation with item cosine similarity

One subtype of information filtering system is known as a recommender system, also known simply as a recommendation system. In the recommendation based on average rating, this type of system attempts to forecast the "rating" or "preference" that a user would assign to an item. The majority of their uses are in the commercial sector.The average Rating Calculation with recommendation based on AVG ratings is given in figure 12. The rating histogram is given in figure 13. Correlation of Rating and Avg Rating based on Rating Count is given in figure 14. The matrix size is 3292 4974. The Top 30 Recommendation and their Rating Count is given in figure 15. The final prediction and Recommendations is given

[('AZZFCZRH7GP7H', 0.0), ('AZYU3UKUITVZV', 0.0), ('AZWMO4VW6GBK7', 0.0), ('AZWBY420OJ2F1', 0.0), ('AZW7PDA9PBDO', 0.0), ('AZVVZ
9SDF4M3O', 0.0), ('AZPPBDFH77E1M', 0.0), ('AZPKIKGDVW9YJ', 0.0), ('AZPK0NHE68BN3', 0.0), ('AZKFG8SOVO3W', 0.0)]

Figure 16: Top 30 Recommendation and their Rating Count

Popularity based recommender system

Popularity based recommender system makes use, for the most part, of the things that are popular at the present time. This is the most fundamental form of recommendation systems, in which a generalised recommendation is given to each user based on how popular that individual is. Whatever is more well-known among members of the general public is the one that will most likely be suggested to new consumers. The matrix Size for the popularity based recommender system is 4980 3324. The prediction and Recommendations of this recommender system is

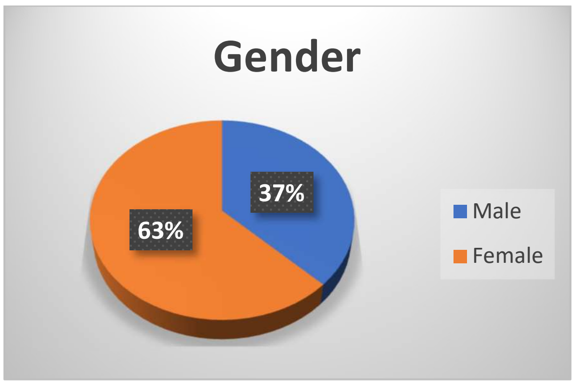

Figure 17: Graphical representation of gender of respondents

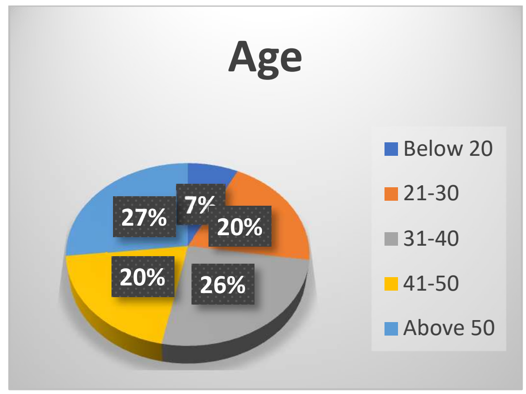

Figure 18: Graphical representation of age of respondents

Figure 17 indicates that out of the total of 150 respondents (or individuals), 56 (37.3%) are identified as male, and 94 (62.7%) are identified as female.

Figure 18 provides an overview of the distribution of respondents' ages within dataset. It indicates that out of the total of 150 respondents, their ages are distributed as follows:

- 11 respondents (7.3%) are below 20 years old.
- 30 respondents (19.9%) are in the age range of 21 to 30.
- 39 respondents (25.4%) are in the age range of 31 to 40.
- 30 respondents (19.9%) are in the age range of 41 to 50.
- 40 respondents (26.5%) are above 50 years old.

5.2 Impact of E-WOM for Social Causes related marketing

Table 1: ANOVA analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.616	4	1.904	37.851	.000[b]
	Residual	7.294	145	0.05		
	Total	14.909	149			
a. Dependent Variable: Average(e-WOM)						
b. Predictors: (Constant), (self connect), Feel good factor, (action factor), average (self reference)						

This is the p-value linked with the F-statistic. A p-value less than 0.05 implies that the regression model is statistically significant.

According to the Regression row, the regression model explains a large amount of variability in the dependent variable "Average(e-WOM)." The F-statistic is 37.851, and the p-value is 0.000, indicating that the regression model is statistically significant. In summary, the ANOVA summary evaluates whether the predictors of the regression model collectively contribute to explaining the variation in the dependent variable. A low p-value for the F-statistic shows that the model is statistically significant and that the predictors influence the dependent variable significantly.

Table 2: Correlation analysis 1

		(e-WOM)	Feel good factor	(self refernce)	(action factor)	(self connect)
(e-WOM)	Pearson Correlation	1	.446**	.611**	.216**	.555**
	Sig. (2-tailed)		0	0	0.008	0
	N	150	150	150	150	150
Feel good factor	Pearson Correlation	.446**	1	.749**	.559**	.726**
	Sig. (2-tailed)	0		0	0	0
	N	150	150	150	150	150
(self reference)	Pearson Correlation	.611**	.749**	1	.649**	.855**
	Sig. (2-tailed)	0	0		0	0
	N	150	150	150	150	150
(action factor)	Pearson Correlation	.216**	.559**	.649**	1	.809**
	Sig. (2-tailed)	0.008	0	0		0
	N	150	150	150	150	150
(self connect)	Pearson Correlation	.555**	.726**	.855**	.809**	1
	Sig. (2-tailed)	0	0	0	0	
	N	150	150	150	150	150
**. Correlation is significant at the 0.01 level (2-tailed).						

The factors mentioned above (e-WOM and social cause marketing) are substantially connected. Pearson link coefficients indicate the degree and direction of the link between two variables. This is the p-value for each correlation coefficient. A p-value less than 0.05 implies that the association is statistically significant. As a result, we discovered a significant connection between e-WOM and social cause marketing.

Table 3:Correlation analysis 2

		(e-WOM)	Gender
(e-WOM)	Pearson Correlation	1	0.83
	Sig. (2-tailed)		.000
	N	150	150
Gender	Pearson Correlation	0.83	1
	Sig. (2-tailed)	.000	
	N	150	150

The table 3 is an expanded version of the correlation matrix that contains the correlation between factors as well as a new variable, "Gender." It displays Pearson correlation coefficients between the e-WOM and the gender variable. Pearson Inc. The correlation coefficient between "(e-WOM)" and "Gender" is 0.83. This suggests that the two variables have a very high positive association. The p-value associated with the correlation is 0.000, suggesting that it is statistically significant at the 0.01 level.

In conclusion, the correlation matrix sheds light on the link between the variables "(e-WOM)" and "Gender." The substantial positive correlation indicates that these two variables in the dataset have a significant linear connection. Furthermore, the statistically significant p-value suggests that this association is unlikely to have happened by coincidence.

As a result, there is a substantial association between e-WOM and social cause marketing marketing, with the gender of the responder mitigating the relationship.

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Table 4: Correlation analysis 3

		(e-WOM)	Age
(e-WOM)	Pearson Correlation	1	.79
	Sig. (2-tailed)		.018
	N	150	150
Age	Pearson Correlation	.79	1
	Sig. (2-tailed)	.018	
	N	150	150

The correlation matrix in table 4 illustrates Pearson correlation coefficients between two variables, "(e-WOM)" (electronic word-of-mouth) and "Age." Pearson Inc. The correlation coefficient between "(e-WOM)" and "Age" is 0.79. This implies a significant positive correlation between the two variables, implying that when one measure grows, so does the other. The p-value associated with the correlation is 0.018, suggesting that the connection is statistically significant at the 0.05 level.

In conclusion, the correlation matrix sheds light on the link between the variables "(e-WOM)" and "Age." The substantial positive correlation and statistically significant p-value indicate that these two variables in the dataset have a meaningful linear connection. So we discovered a substantial link between e-WOM and social cause marketing moderating with respondent age.

6. Conclusion

The role of artificial intelligence in business and society is growing. In particular, recommendation systems built using AI have become an integral part of our everyday lives. Algorithms, according to a number of studies, can do sophisticated and analytical jobs more quickly and cheaply than people can. Despite the fact that algorithms often surpass human performance on a variety of jobs, many individuals are still reluctant to use them. First, we suggest the use of TensorFlow Recommender (TFRS) to investigate the effects of an AI-powered recommendation system on the expansion of electronic word of mouth (E-WOM). As a result, we have presented a systematic approach to investigate the effects of AI-powered recommendation systems on improving E-WOM.

In the study's second investigation, researchers discovered that females play a significant role in electronic word-of-mouth (e-WOM) for social causes marketing. In conclusion, women's empathy, influence, and networking skills make them ideal agents for propagating e-WOM for social causes. Their participation may boost understanding, advocacy, and action on critical social problems. For groups and activists working to effect good change via social marketing, an appreciation of women's viewpoints and contributions is crucial. How people of different ages interact with and support social issues through electronic word of mouth (e-WOM) may have far-reaching consequences. Our research shows that people over the age of 50 are particularly influential in the rea lm of e-word-of-mouth (e-WOM) for humanitarian causes. By participating in e-WOM via email, discussion forums, and blogs, people of retirement age may add their voices to the chorus of those advocating for social change. Participation from the elderly in e-WOM may encourage conversations across generations about important societal issues, bringing new ideas and insights to the table. People in their latter years may utilise e-WOM to provide valuable historical perspective to discussions about persistent societal challenges. No matter how old you are, authenticity is the key to successful e-WOM. It's crucial to find a happy medium between being genuine and appealing to a wide range of age groups. To sum up, different people of different ages have different tastes, levels of involvement, and ways of interacting when it comes to e-WOM for social reasons.

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